

A METHOD OF MODELING SINGLE-ENROLLMENT CLASSES IN
VERIFICATION AND IDENTIFICATION TASKS

Field of the Invention

The present invention relates to problems in automatic pattern recognition systems
5 (for example speaker or speech recognition systems), arising with patterns (that are to be
classified as one of the previously seen [enrolled] classes) being observed either in the
same or a new environment, e.g., a new acoustic channel, as compared to the one seen
during the previous enrollment.

Background of the Invention

10 An example of the latter situation, as set forth above, is a voiceprint recognition
task for a speaker (class) previously enrolled using speech samples collected over a
microphone of a type A but later being tested on samples recorded over a microphone
type B. It has been widely recognized that environment/channel mismatches cause more
or less great a degradation of the system recognition accuracy and represent one of the
15 major challenges in the pattern recognition area. This is covered in at least the following
references: "HTIMIT and LLHDB: Speech Corpora for the Study of Handset Transducer
Effects", International Conference on Acoustics, Speech, and Signal Processing, Munich,

Germany, May 1997, by D.A. Raynolds (microphone mismatch in speech recognition);
and “The IBM system for the NIST 2002 cellular speaker verification evaluation”,
International Conference on Acoustics, Speech, and Signal Processing, Hong Kong, April
2003, by G.N. Ramaswamy et al. (state of the art technology, including mismatched
5 conditions). A need has thus been recognized in connection with solving such problems,
among others.

Summary of the Invention

In accordance with at least one presently preferred embodiment of the present
invention, there is broadly contemplated herein a method which helps to do the following:

10 reduce the negative impact of the mismatched environment mentioned above and
makes recognition systems more robust in real-world scenaria where the environment
conditions change very often;

eliminate the need for additional data from every particular new environment (i.e.,
adaptation data) for every particular enrolled model, but rather achieve such adaptation
15 using data independent from the enrolled model population (keeping in mind that in many
practical systems a single enrollment of a target model, as opposed to enrollment in
multiple environments, is the only choice);

improve the performance in matched conditions (i.e., same environment); and

hide data, allowing for class enrollments without storing the actual feature measurements, thus being useful as an implicit data hiding/model encryption method.

In summary, the present invention provides, in one aspect, an apparatus for
5 performing pattern recognition, the apparatus comprising: an input arrangement which
inputs features; a base model provision arrangement which provides at least one base
model; an environment detector which ascertains an environment from which the at least
one base model originated; and a transform arrangement which produces a target model
based on a feature vector corresponding to the environment from which the at least one
10 base model originated.

In another aspect, the present invention provides a method of performing pattern
recognition, the method comprising the steps of: inputting features; providing at least one
base model; ascertaining an environment from which the at least one base model
originated; and producing a target model based on a feature vector corresponding to the
15 environment from which the at least one base model originated.

Furthermore, in an additional aspect, the present invention provides a program
storage device readable by machine, tangibly embodying a program of instructions

executable by the machine to perform method steps for performing pattern recognition,
the method comprising the steps of: inputting features; providing at least one base model;
ascertaining an environment from which the at least one base model originated; and
producing a target model based on a feature vector corresponding to the environment
5 from which the at least one base model originated.

For a better understanding of the present invention, together with other and further
features and advantages thereof, reference is made to the following description, taken in
conjunction with the accompanying drawings, and the scope of the invention will be
pointed out in the appended claims.

10 **Brief Description of the Drawings**

Fig. 1 schematically illustrates a training base and target models; and

Fig. 2 schematically illustrates environment compensation in testing.

Description of the Preferred Embodiments

An underlying concept utilized for channel mismatch compensation, in
15 accordance with at least one preferred embodiment of the present invention, is the
cascading of two model levels. In this scenario, a set of M generative base (or
background) models (e.g., background speakers) is created. These models may be of any

type, for example Gaussian Mixture Models (see “Finite Mixture Models”, by Geoffrey McLachlan and David Peel, ISBN: 0-471-00626-2, 2000); however, by definition, they must provide a measure of sample generation "likeliness", wherein statistical models will provide likelihood which is directly connected to the notion of probability density, while

5 non-statistical models will provide another type of scores to express the measure of closeness. The base models can be viewed as complex, generally non-linear trainable D-to-1 functions of the D-dimensional input feature space. In the second stage, another level of models is preferably built using the M output scores generated by the base models as input. Now, assuming the base models are trained and available for an environment A,

10 using some training data set X (set of feature vectors) of a target class (e.g. a target speaker) from environment A, M scores can be calculated for each such feature vector, thus forming an M-dimensional meta-feature vector. This is formulated as a transform of the set X to $X' \left((f_a : \mathbb{R}^D \rightarrow \mathbb{R}^M, X' = f_A(x)) \right)$. The transformed X' training set is then used to train a meta-model for the target class, given the environment A.

15 Next, assume a test comes through a microphone/channel $B \neq A$, and there exists a corresponding set of base models (part of the system) that were trained in condition B. If the information about the channel identity (B) is explicitly available (in many real applications it is, for example in digital telephony the codec and device type can be

extracted), then the channel compensation is achieved by carrying out a transform

$f_B : \mathbb{R}^D \rightarrow \mathbb{R}^M, X' = f_B(X)$, i.e., by calculating the base scores on the set of B-

channel base models and using their output scores as input to the stacked model for the target class (or classes), previously trained in environment A. The effect of the new

5 transform is that a possible mismatch in feature relationships present in environment A (and learned by the target class in the same) is mitigated by exchanging f_A by f_B and therefore adapting the target feature space to the new environment, which helps restore the originally observed feature relationships and thus reduce the mismatch.

In cases where there is no explicit information about the environment type of the
10 test, a maximum-likelihood method can be utilized at test time on multiple base sets to decide which environment is the most likely to be the one of the test sample. (See “Pattern Classification, Second Edition”, by R.O. Duda, P.E. Hart, and D.G. Stork, John Wiley and Sons, 2000).

An important point in the above-discussed adaptation is the independence of the
15 base set and the target model, which allows for a single enrollment of the target class.

The stacked model can be used in combination with a model for the same target class created in the D-dimensional original feature space. The combination may help

prevent information loss in cases when M is chosen to be small (particularly $M < D$), i.e. in case when a dimensionality reduction is achieved by the function f . In the combination, the performance of both models is utilized and, depending on the degree of mismatch, the focus may be dynamically shifted, from/to the base target model to/from the stacked

5 model. In a heavily mismatched environment, the base target model will show poor accuracy and hence the stacked and compensated model will be emphasized, and vice versa. An example of such a dynamic combination is a linear interpolation of the base target model score (S_{T0}) and the stacked target model score (S_{T1}):

$$S = w_0(c)S_{T0} + w_1(c)S_{T1} \quad (1.1)$$

10 with w denoting the weight factors that are a function of the channel/environment c .

The principal steps discussed above may preferably be exercised on an example of a speaker verification system including Gaussian Mixture Models (GMM) representing the two classes: 1) the target speaker, and 2) the “world” (or background) model. As stated above however, the method is nonetheless applicable to essentially any

15 classification problem involving two or more classes, represented by either by GMMs or by means of other model structures.

The verification task is posed as a binary hypothesis problem involving two classes as mentioned above. Let M_T and M_W denote the target and the world GMM model respectively, and let $L(X|M)$ be the likelihood measure for an acoustic utterance X to be generated by a model M . In the present (illustrative and non-restrictive) example,

5 L shall be the generative log-probability density of the model.

To arrive at a verification decision, i.e. to either accept or reject the utterance X as being spoken by the target speaker or not, typically the likelihood ratio between the target and the world model is calculated as follows:

$$\Lambda(X) = L(X|M_T) - L(X|M_W) \quad (2.1)$$

10 (see “Speaker Identification and Verification Using Gaussian Mixture Speaker Models,”
 17 Speech Communication 91-108 (1995) by D.A. Reynolds) which then serves as basis
 for the threshold operation:

$$\text{accept when } \Lambda(X) \geq \vartheta, \text{ otherwise reject} \quad (2.2)$$

with ϑ being the decision threshold that controls the system bias towards more

15 acceptances or more rejections.

Furthermore, the likelihood of the world model can be composed from many individual GMMs; in particular, it can be effectively approximated by a small number of models whose speakers are similar to the target speaker (so-called cohort speakers, or cohorts). Thus, an average likelihood replaces that of the world model in the likelihood ratio (2.1):

$$\Lambda(X) = L(X|M_T) - \frac{1}{N} \sum_{i=1}^N L(X|M_{C_i}) \quad (2.3)$$

Assume a set of K base GMMs, denoted B_{A1}, \dots, B_{AK} , are used as the base models to realize the transform function f described above, trained in the environment A. Also, such sets exist for environments B, C, ..., etc. Then the models M_T and $M_{C_i}, i = 1, \dots, N$ are created using corresponding training sets of feature vectors in environment A:

$$X' = \{L(X|B_{A1}), \dots, L(X|B_{AK})\}.$$

In a test occurring in the environment B the feature vectors are obtained as:

$$X' = \{L(X|B_{B1}), \dots, L(X|B_{BK})\},$$

etc.

By way of summary, the following steps maybe undertaking to build a system and to carry out the compensation described hereinabove:

1. Build a pool of base models of the system (GMM) using standard techniques, e.g., as described in “Pattern Classification, Second Edition”, by R.O. Duda, P.E. Hart,
5 and D.G. Stork, John Wiley and Sons, 2000.

2. Define a discriminant function $L(X|B)$, which expresses the closeness of a sample X to a given base model B .

3. Using an appropriate algorithm, select a set of K GMM base models $S = \{B_1, \dots, B_K\}$ from the global pool of models (Step 1). An example of such an
10 algorithm is selecting the K closest models M_{C_1}, \dots, M_{C_N} given a target mode.

4. Define a K -dimensional space in \mathbb{R}^K such that its bases are constituted by functions of the likelihoods on the selected model set, i.e. the function f mentioned above, for each known environment A, B, \dots , etc.

5. Transform the training data of the target model M_T using f for the matching
15 environment (A), i.e. using f_A .

6. Create a GMM using the transformed training set.
7. Repeat steps 5,6 for all cohort models M_{C_1}, \dots, M_{C_N} , using cohort training data.
8. For a new test in environment B, transform the test feature vectors using f_B and calculate the likelihood using the GMM (target and cohorts) created in Step 6. and
5 calculate the likelihood ratio as in Eq. (2.3).
9. (Optional) Combine the likelihood from Step 8 with a likelihood of a standard verification system using the original, uncompensated feature space, for example as in (1.1).

A system overview, schematically illustrated in Figure 1 (depicting training) and
10 Figure 2 (depicting testing), provides an additional convenient summary of the foregoing discussion. As shown in Fig. 1, target model training data in environment A (102) provides input features X (104) which, when combined with the base model training data of environment A (106), yields base models 1, 2...K (108). The target model (112) is then created using transformed features X' (110).

15 Fig. 2 illustrates environment compensation during testing. As shown, upon the provision of input features X (104), automatic environment detector 114 will, depending

on whether environment A, B or another environment is detected, inform resolution of the feature vector 110 used in creating the target model 112.

It is to be understood that the present invention, in accordance with at least one presently preferred embodiment, includes an input arrangement which inputs features, a
5 base model provision arrangement which provides at least one base model, an environment detector which ascertains an environment from which the at least one base model originated, and a transform arrangement which produces a target model based on a feature vector corresponding to the environment from which the at least one base model originated. Together, these elements may be implemented on at least one general-purpose
10 computer running suitable software programs. These may also be implemented on at least one Integrated Circuit or part of at least one Integrated Circuit. Thus, it is to be understood that the invention may be implemented in hardware, software, or a combination of both.

If not otherwise stated herein, it is to be assumed that all patents, patent
15 applications, patent publications and other publications (including web-based publications) mentioned and cited herein are hereby fully incorporated by reference herein as if set forth in their entirety herein.

Although illustrative embodiments of the present invention have been described herein with reference to the accompanying drawings, it is to be understood that the invention is not limited to those precise embodiments, and that various other changes and modifications may be affected therein by one skilled in the art without departing from the
5 scope or spirit of the invention.